

# Direct Yaw Moment Control of an In-Wheel-Motored Electric Vehicle Based on Body Slip Angle Fuzzy Observer

Cong Geng, Lotfi Mostefai, Mouloud Denaï, and Yoichi Hori

**Abstract**— A stabilizing observer based control algorithm for an in-wheel-motored vehicle is proposed, which generates direct yaw moment to compensate for the state deviations. The control scheme is based on a fuzzy rule-based body slip angle ( $\beta$ ) observer. In the design strategy of the fuzzy observer, the vehicle dynamics are represented by Takagi-Sugeno-like (T-S) fuzzy models. Initially, local equivalent vehicle models are built using linear approximations of vehicle dynamics respectively for low and high lateral acceleration operating regimes. The optimal  $\beta$  observer is then designed for each local model using Kalman filter theory. Finally, local observers are combined to form the overall control system by using fuzzy rules. These fuzzy rules represent the qualitative relationships among the variables associated with the nonlinear and uncertain nature of vehicle dynamics, such as tire force saturation and the influence of road adherence. An adaptation mechanism for the fuzzy membership functions has been incorporated to improve the accuracy and performance of the system. The effectiveness of this design approach has been demonstrated in simulations and in a real-time experimental setting.

**Index Terms**— fuzzy observer, local modeling, vehicle lateral dynamics, state feedback.

## I. INTRODUCTION

This paper focuses on the design of control strategies to enhance the performance and safety of electric vehicles in critical driving situations. It has been commonly recognized that electric vehicles (EVs) are inherently more suitable to realize active safety stability control over conventional Internal Combustion engine Vehicles (ICVs). In EVs, the motor torque can be measured and controlled accurately; and in-wheel motors can be installed in each EVs' rear and front tires. Based on these structural merits, vehicle motion can be stabilized by additional yaw moment generated as a result of the difference in tire driving or braking forces between the right and left side of the vehicle, which is so called 'Direct Yaw-moment Control' (DYC) [1]-[5].

Fig.1 shows the main concept of the chassis control system utilizing DYC based on the model matching control method and optimal control method [3] [4] [6].

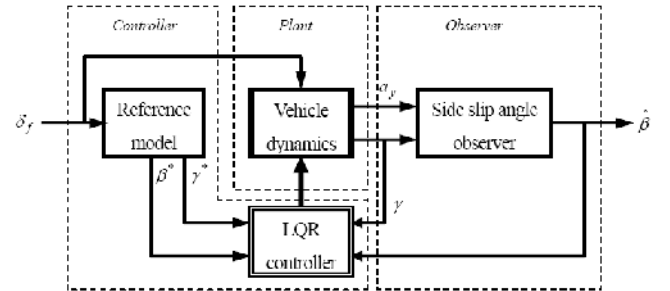


Fig.1 Vehicle lateral stability control structure.

This system is aimed to maintain the driver's handling ability at the physical limit of adhesion between the tires and the road by making the vehicle easily controllable even well below that limit. The dynamics of the 2-DOF (Degree Of Freedom) vehicle model can describe the driver's familiar characteristics under normal driving conditions. The body slip angle ( $\beta$ ) and yaw rate ( $\gamma$ ) calculated from the model are taken as the desired behavior of the vehicle. By applying Model Matching Control, the yaw moment optimal decision can be derived from the deviations of the state feedback compensator of  $\beta$  and  $\gamma$  from their desired values. Since sensors for the direct measurement of  $\beta$  are very expensive, the construction of an observer for its estimation is desirable.

Generally, such state feedback control method is based on the state equations derived from the vehicle dynamics. However, the implementation of these techniques are still difficult since the vehicle dynamics are highly nonlinear, especially for  $\beta$ . Previous authors' approaches regarding  $\beta$  estimation issue used model-based observers with either linear or nonlinear equivalent vehicle dynamic models [6]-[8], [9], [10]. With regard to linear observer design, the linear 2-DOF vehicle model with fixed parameters is adopted. However, this approach can not always achieve accurate results in different running situations. In the design of nonlinear observers, tires characteristics are described by nonlinear functions and with more parameters, which can produce relatively more accurate results in different running situations compared with linear

observers. However, nonlinear observers have the disadvantages of not having a strong theoretical maturity and still face difficulties regarding their realtime implementation.

The main nonlinearity of vehicle dynamics comes from the tire force saturation imposed by the limits of tire adherence, which makes  $\beta$  response change considerably if the vehicle is cornering much more than usual. In other words, the model structure or model parameters should vary according to the different operating regimes for a more practical controller design. In addition, the nonlinear nature of vehicle dynamics is further complicated by the influence of the characteristics of whole chassis elements (tires, suspensions and steering system). It is hard to determine the physical model parameters theoretically. Therefore, an effective modeling methodology is the key for the system design.

To deal with the difficulties associated with nonlinearity modeling, as well as to make use of the linear observer advantages such as simplicity in the design and implementation, the nonlinear vehicle dynamics are represented by Takagi-Sugeno (T-S) fuzzy models [11], [12]. Local approximation of the nonlinear vehicle model and a dynamical interpolation method is introduced in this paper to construct a fuzzy model-based control system for  $\beta$  estimation and control. Optimal  $\beta$  observer is designed for each local model using Kalman filter theory. The proposed system is a combination of local linear observers and controllers with varying switching partition.

The first step in the design is concerned with the derivation of the system state equations from the vehicle dynamics and local approximation of nonlinear tire model. These modeling techniques are considered appropriate for on-line control system design (linear 2-DOF vehicle model as in [13]). In the next step, a fuzzy-based modeling approach is used to get a hybrid-like vehicle model which is calculated as a weighted sum of the outputs of two local linear models. For practical applications, parameter identification is conducted experimentally. An adaptation mechanism of the fuzzy membership functions has been included to make the model fit different running conditions and road friction changes. The membership functions of the weighting factors are chosen to be dependent on lateral acceleration and road friction coefficient. The two local observers are based on local linear tire models, which inherently leads to a relatively simple design, have been combined into a single overall observer by means of fuzzy rules. Furthermore, the nonlinear global system results show high  $\beta$  estimation capabilities and good adaptation to changing road friction. A series of simulations are performed to evaluate the effectiveness of the proposed  $\beta$  observer when incorporated into a DYC-based control scheme.

## II. VEHICLE DYNAMICS AND FUZZY MODELING

### A. Local Approximation and Linearization of Vehicle Dynamics

The system is based on an in-wheel-motored electric vehicle dynamics model (Fig. 2). The main difference with common vehicle dynamics is that the direct yaw moment is an additional

input variable, which is caused by individual motor torque between each wheel.

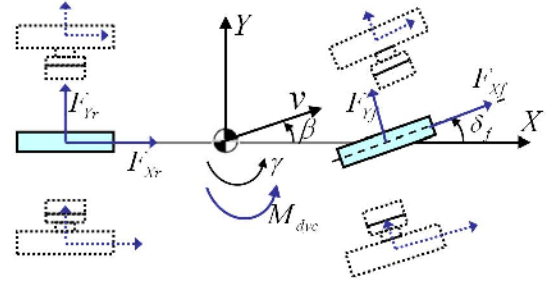


Fig.2 2-DOF vehicle model.

The vehicle dynamics are approximately described by the following 2-DOF vehicle model equations:

$$\begin{aligned} \bullet \quad m a_y &= F_{xf} \sin \delta_f + F_{yf} \cos \delta_f + F_{yr} \\ \bullet \quad I_z \dot{\gamma} &= l_f F_{xf} \sin \delta_f + l_f F_{yf} \cos \delta_f + l_r F_{yr} + N \end{aligned} \quad (1)$$

Where  $a_y$  denotes the vehicle lateral acceleration,  $\gamma$  is the yaw rate,  $\delta_f$  is the steering angle of the front wheel,  $N$  is the direct yaw moment,  $m$  represents the mass of the vehicle,  $I_z$  is the yaw inertia moment,  $l_f$  denotes the distance between the centre of the mass and the front axle,  $l_r$  is the distance between the centre of mass and the rear axle,  $F_{xf}$  is the longitudinal force of the front tires,  $F_{yf}$  and  $F_{yr}$  are the lateral forces of the front and rear tires respectively.

Let the body slip angle  $\beta$  and yaw rate  $\gamma$  represent the system state variables. By defining the kinematics relationship as  $a_y = v(\dot{\beta} + \gamma)$  and assuming that  $\delta_f$  is relatively small for high speeds, the vehicle's state equations are obtained as:

$$\begin{aligned} \bullet \quad \dot{\beta} &= \frac{1}{mv} (F_{yf} + F_{yr}) \cdot \hat{\gamma} \\ \bullet \quad \dot{\gamma} &= \frac{1}{I_z} (l_f F_{yf} + l_r F_{yr} + N) \end{aligned} \quad (2)$$

The model of equation (2) is nonlinear due to the tire lateral force dynamics. By using local operating regime approximations, the model can be simplified into an equivalent linear 2DOF model by adopting the equivalent tire cornering stiffness  $C$ , which is defined by:

$$C = \frac{F_y}{\alpha} \quad (3)$$

Where  $F_y$  is the tire lateral force and  $\alpha$  is the tire slip angle at its operating point.

By adopting the value of  $C$  given by (3), the nonlinear vehicle dynamic state equations (2) can be transformed into the

following equivalent linear state equations at the local operating point:

$$\dot{x} = Ax + Bu \quad (4)$$

In which,

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} = \begin{bmatrix} \frac{(2C_f + 2C_r)}{mV} & \frac{2l_f C_f + 2l_r C_r}{mV^2} \\ \frac{2l_f C_f + 2l_r C_r}{I_z} & \frac{2l_f^2 C_f + 2l_r^2 C_r}{I_z V} \end{bmatrix}$$

$$B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} = \begin{bmatrix} \frac{2C_f}{mV} & 0 \\ \frac{2l_f C_f}{I_z} & \frac{1}{I_z} \end{bmatrix}$$

$$x = \begin{bmatrix} \beta \\ \gamma \end{bmatrix}, u = \begin{bmatrix} \delta_f \\ N \end{bmatrix}$$

Where,  $C_f \sim C_r$  are the cornering stiffness values of the front and rear tires respectively,  $V$  is the longitudinal velocity.

Since the main nonlinearity in the model comes from the tires, the cornering stiffness of the tires will play an important role in the formulation of the model used in the estimator. According to Fig. 3, these coefficients are large when the tire slip angle assumes small values, which are equivalent to the low lateral acceleration regimes; on the other hand, the stiffness coefficients become small when the tire slip angle increases which means that the vehicle is running at high lateral accelerations. Hence, to describe the vehicle dynamics by an equivalent linear 2-DOF model, local models with different  $C$  value should be considered, for both low and high lateral accelerations.

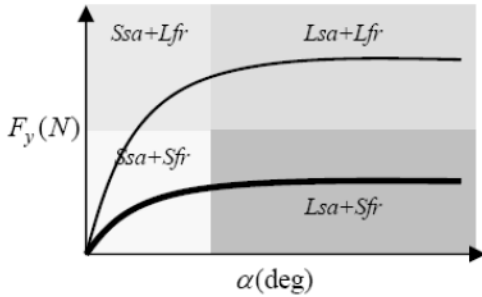


Fig. 3 Tire lateral force characteristics partitioned roughly into 4 different local dynamics (Lsa: large tire slip angle, Ssa: small tire slip angle, Lfr: large friction, Sfr: small friction).

#### B. Model Parameters Identification

For the local dynamic models, the equivalent tire cornering stiffness,  $C_f \sim C_r$ , are difficult to determine theoretically because their values are influenced by the suspension dynamics, tire characteristics and steering system. In this paper, an identification method of tire cornering stiffness based on experimental tests performed on the electric vehicle is proposed.

According to (2), the steady state cornering relationship with steering angle input can be expressed as follows:

$$\begin{aligned} \bullet \quad ma_y &= F_{yf} + F_{yr} \\ \bullet \quad 0 &= l_f F_{yf} - l_r F_{yr} \end{aligned} \quad (5)$$

From (5), the expression of the side force applied to the front and rear tires can be deduced as:

$$\begin{aligned} \bullet \quad \hat{F}_{yf} &= \frac{l_r}{l} ma_y \\ \bullet \quad \hat{F}_{yr} &= \frac{l_f}{l} ma_y \end{aligned} \quad (6)$$

And the body slip angle of front and rear tires can be obtained as:

$$\begin{aligned} \bullet \quad \hat{\alpha}_f &= \beta + \frac{l_f}{V} \dot{\beta} \\ \bullet \quad \hat{\alpha}_r &= \beta + \frac{l_r}{V} \dot{\beta} \end{aligned} \quad (7)$$

If  $\alpha_y$ ,  $\beta$ ,  $\gamma$  are measured from steady state cornering experiments, it follows from the above equations that the tire cornering stiffness can be obtained as:

$$\begin{aligned} \bullet \quad \hat{C}_f &= \frac{F_{yf}}{2\alpha_f} \\ \bullet \quad \hat{C}_r &= \frac{F_{yr}}{2\alpha_r} \end{aligned} \quad (8)$$

For the nonlinearity of vehicle dynamics, cornering experiments with low and high  $\alpha_y$  should be conducted respectively to identify the different cornering stiffness values in different operating regimes.

#### C. Fuzzy Modeling and Local Dynamics

To simplify the fuzzy modelling procedure, the lateral acceleration  $\alpha_y$  will be assigned two fuzzy sets (large and small) as shown in Fig.4.

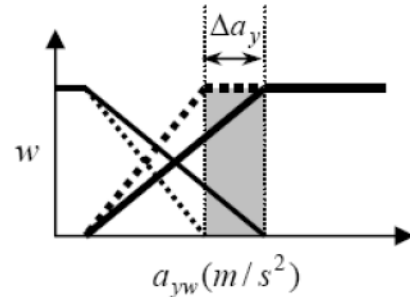


Fig.4 Membership functions adaptation to the lateral acceleration.

Then, using these fuzzy sets, the fuzzy IF-THEN rules for the vehicle dynamics model can be defined as follows:



Rule  $i$ : (local model  $i$ ) IF  $|a_y|$  is  $F_i$ , THEN  $\dot{x} = A_i x + B_i u$

The overall vehicle dynamics are described by two models that take the form of equation (4). The model parameters namely the equivalent tire cornering stiffness are identified according to the steady state regime given by (8).

For the local model 1, the tire works at its small slip region,  $A_1$  and  $B_1$  are calculated based on the largest value of the cornering stiffness  $C$ . For the local model 2, the tire works at its large slip region,  $A_2$  and  $B_2$  are calculated for a relatively small value of the cornering stiffness  $C$ .

Finally, the whole nonlinear dynamics of the vehicle are described with the proposed dynamic switching partition by interpolating the two models with fuzzy logic. By a proper choice of the membership function, the vehicle dynamics can be calculated for different operating regimes (from low  $a_y$  value to high  $a_y$  value).

Therefore, the following equation is used to represent the fuzzy models covering the vehicle dynamics:

$$\dot{x} = \sum_{i=1}^2 w_i (A_i x + B_i u) \quad (9)$$

Where  $w_1$  and  $w_2$  are the membership functions for local model 1 and local model 2. For design simplicity, trapezoidal membership functions have been used. The formulation of  $w_1(a_y)$  and  $w_2(a_y)$  are as follows:

$$w_1(a_y) = \begin{cases} 1 \cdot \frac{1}{a_{yw}} a_y & |a_y| \leq a_{yw} \\ 0 & |a_y| > a_{yw} \end{cases} \quad (10)$$

$$w_2(a_y) = \begin{cases} \frac{1}{a_{yw}} a_y & |a_y| \leq a_{yw} \\ 1 & |a_y| > a_{yw} \end{cases} \quad (11)$$

Where the coefficient  $a_{yw}$  describes the value of  $a_y$  at the tire/road adherence limit (road friction coefficient  $\mu$ ) when the tire force is saturated which is equivalent to severe steering dynamics.

Road condition is one of the most important factors that must be considered in vehicle dynamic stability control, since the road friction coefficient  $\mu$  is uncertain and may change according to the road condition, the fuzzy partition describing the vehicle model must be adaptive to such variations (Fig.4).

The value of  $\mu$  can be identified with different methods. In EVs stability control, one method that the authors adopted previously is to identify  $\mu$  value by analyzing wheel rotation dynamics, which takes advantage of accurate knowledge of the EVs motor torque values [14], [15]. With the identified  $\mu$  value,

$a_{yw}$  is used as a tuning parameter of the weighting functions partition to form an adaptation mechanism to cope with the variation of tire/road adherence conditions. In this work,  $a_{yw}$  is set to be a linear function of  $\mu$  with the following low pass filter to remove the noise:

$$a_{yw} = k_\mu \frac{1}{1 + T_f s} \mu \quad (12)$$

Where  $k_\mu$  is the adaptation gain,  $T_f$  is the constant of 1<sup>st</sup> order low-pass filter.

### III. $\beta$ OBSERVER DESIGN BASED ON FUZZY MODELS

#### D. Kalman Filter for Local $\beta$ Observer Design

Based on the local linear models, the  $\beta$  observer is designed with Kalman filter theory [16]-[18]. For the real-time implementation of the design strategy, the continuous-time model of (4) is converted into discrete time model by taking into account process noise and measurement noise as follows:

$$\begin{aligned} x[n+1] &= G_i x[n] + H_i u[n] + \omega[n] \\ y[n] &= C_i x[n] + D_i u[n] + \nu[n] \end{aligned} \quad (13)$$

Where the covariance vector of process and measurement noise are assumed to be the same for all dynamics:

$$E(\omega[n]\omega[n]^T) = Q, E(\nu[n]\nu[n]^T) = R \quad (14)$$

The sampled equations with a zero-order hold are obtained as:

$$G_i = \begin{bmatrix} 1 + T_s a_{i11} & T_s a_{i12} \\ T_s a_{i21} & 1 + T_s a_{i22} \end{bmatrix}, H_i = \begin{bmatrix} T_s b_{i1} & T_s b_{i2} \\ T_s b_{i1} & T_s b_{i2} \end{bmatrix} \quad (15)$$

Where  $T_s$  is sampling time.

Using the discrete state space equation (13), a discrete form of Kalman estimator can be applied for each linear observer. The vehicle lateral acceleration  $a_y$  and yaw rate  $\gamma$  are two measurable variables and are chosen as output variables of the observer.

$$y = \begin{bmatrix} \gamma \\ a_y \end{bmatrix}, C = \begin{bmatrix} 0 & 1 \\ v a_{11} & v(a_{12} + 1) \end{bmatrix}, D = \begin{bmatrix} 0 & 0 \\ v b_{11} & 0 \end{bmatrix} \quad (16)$$

The recursive discrete Kalman filter algorithm is then applied separately to estimate local dynamics as illustrated by Fig. 5.

Where  $\hat{x}$  and  $\hat{y}$  are the estimates of  $x$  and  $y$  respectively,  $L_i$  is the feedback gain of local observer which is derived using Kalman filter theory.



better estimation, follows closely the real values and has even the ability to adapt to different road friction conditions.

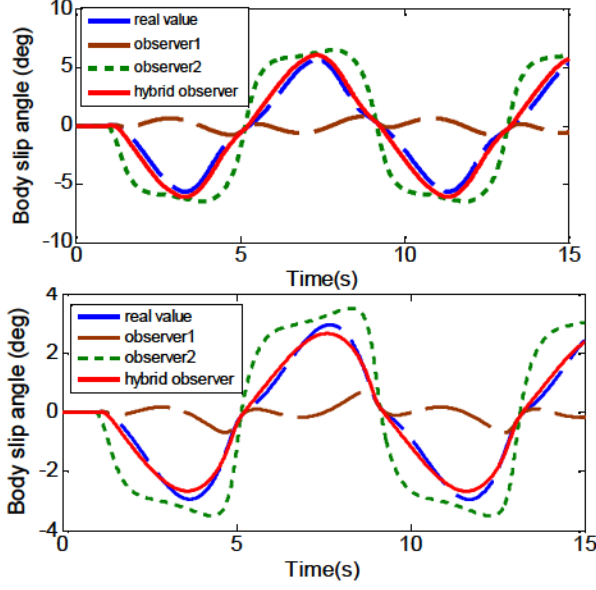


Fig. 8 Simulation results of the hybrid observer under large road friction situation ( $\mu = 0.85$ ) (top panel) and small road friction situation ( $\mu = 0.4$ ) (bottom panel).

To evaluate the proposed control scheme under more realistic conditions, field tests are conducted on our experimental Electric Vehicle “UOT March II”. UOT March II is equipped with an acceleration sensor, a gyro sensor and a noncontact speed meter which provide measurements of the vehicle state variables.

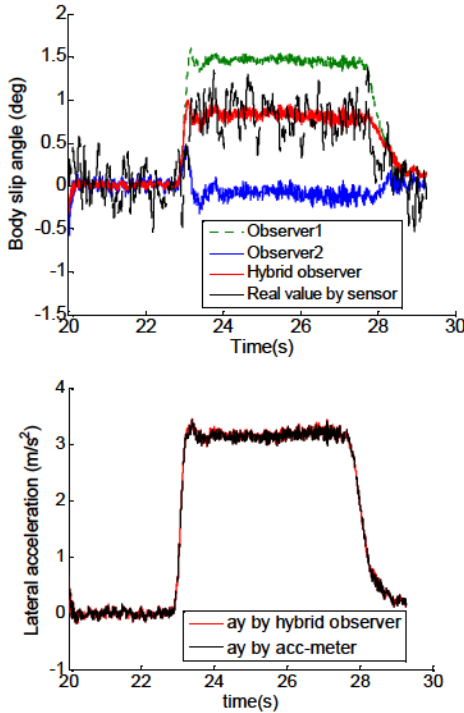


Fig. 9 Experimental field test results of  $\beta$  observer (steering angle=90°, v=40km/h).

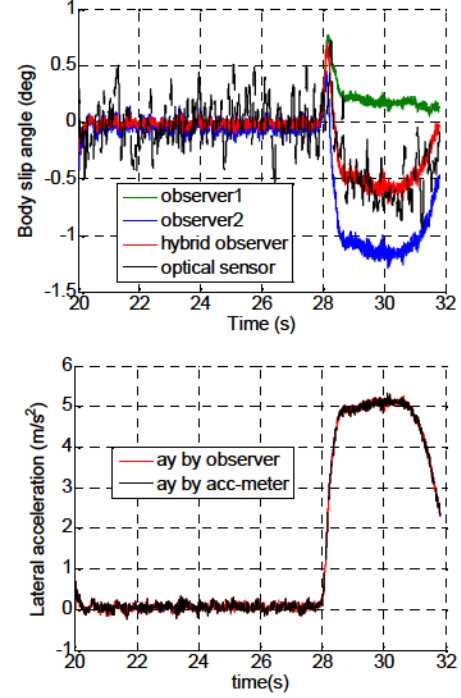


Fig. 10 Experimental field Test results of  $\beta$  observer (steering angle=90°, v=60 km/h).

Fig. 9 and 10 are the results of field tests of the observer in moderate and severe cornering situations. The experiments demonstrate that the observer is very effective and suitable for real time applications due to its high on-board computational speed.

## V. SIMULATION OF OPTIMAL YAW MOMENT CONTROL BASED ON THE PROPOSED $\beta$ OBSERVER

### A. Desired Model and State Deviations Equation

As shown in Fig.1, the control scheme is applied for DYC system design by using the model matching control method.

The desired state variables of  $\beta$  and  $\gamma$  are determined by a 2-DOF linear model with front wheel steering angle as input according to (4) and are expressed as follows:

$$\begin{bmatrix} \dot{\beta}_d \\ \dot{\gamma}_d \end{bmatrix} = A \begin{bmatrix} \beta_d \\ \gamma_d \end{bmatrix} + \begin{bmatrix} b_{11} \\ b_{21} \end{bmatrix} \delta_f \quad (18)$$

In addition,  $\gamma$  should be constrained by its adhesion saturation value as follows:

$$\gamma_d \leq \frac{\mu g}{V} \quad (19)$$

The state deviations variable between the desired value  $X_d$  and actual value  $X$  is assumed to be as follows:



$$E = X \cdot X_d = \begin{bmatrix} \ddot{\beta} \\ \ddot{\gamma} \end{bmatrix} = \begin{bmatrix} \ddot{\beta} \cdot \beta_d \\ \ddot{\gamma} \cdot \gamma_d \end{bmatrix} \quad (20)$$

According to (4) and (18), the differentiation of the above equation leads to the error dynamics:

$$\dot{E} = \dot{X} \cdot \dot{X}_d = A \cdot E + \begin{bmatrix} b_{12} \\ b_{22} \end{bmatrix} N \quad (21)$$

Equation (21) describes the dynamic relationship between the direct yaw moment and vehicle motion state deviations. It shows that when a vehicle motion deviations appears, exerting a direct yaw moment can reduce them to make the vehicle regain stability.

#### B. Optimal Yaw Moment Decision algorithm

Based on the Linear Quadratic Regulator (LQR) method, the optimal control input can be calculated by state feedback deviations as follows:

$$N^* = k_1(\beta \cdot \beta_d) + k_2(\gamma \cdot \gamma_d) \quad (22)$$

Where the feedback gains  $k_1$  and  $k_2$  related to the local model are determined so that the following performance index is minimised:

$$J = \frac{1}{2} \int_0^\infty [q_1 \cdot \beta^2(t) + q_2 \cdot \gamma^2(t) + N^2(t)] dt \quad (23)$$

Where  $q_1$  and  $q_2$  are weighting coefficients of the state deviations which can be chosen to modulate the controller sensitivity with respect to  $\beta$  and  $\gamma$  deviations. For this purpose, the coefficient  $\omega_\beta$  ( $0 \leq \omega_\beta \leq 1$ ) is introduced in the performance index as a weighting factor on  $\beta$  deviation. We define  $q_1 = q^2 \omega_\beta$  and  $q_2 = q^2(1 - \omega_\beta)$ , and (23) can be rewritten as:

$$J = \frac{q}{2} \int_0^\infty [\omega_\beta \cdot \beta^2(t) + (1 - \omega_\beta) \cdot \gamma^2(t) + N^2(t)] dt \quad (24)$$

Small values of  $\beta$  produce a more important  $\gamma$  matching control whereas larger values lead to a more important  $\beta$  control. In addition, the vehicle stability is more sensitive to  $\beta$  deviation under low adhesion road conditions than it is under high adhesion road conditions. Therefore,  $\omega_\beta$  is dependant on  $\beta$  and the road friction coefficient  $\mu$  and is chosen as follows:

$$\omega_\beta = \begin{cases} \frac{|\beta|}{\mu \times \beta_0} & \text{if } |\beta| < \mu \times \beta_0 \\ 1 & \text{else} \end{cases} \quad (25)$$

Where  $\beta_0$  is a threshold value which has been set to  $10^\circ$  based on the authors' experience.

The graph of  $\omega_\beta$  as a function of  $\beta$  is plotted in Fig. 11.

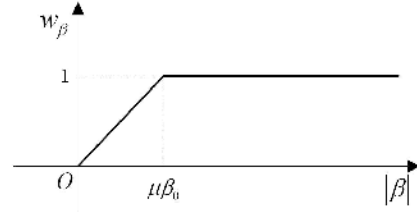


Fig. 11 Weight of body slip angle deviation for optimal yaw moment decision.

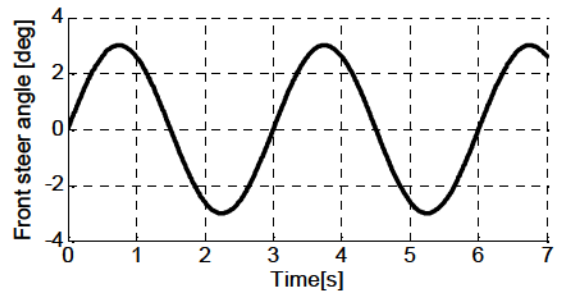
#### C. Simulation Results of Body Slip Angle Control

In the following simulations, a full four wheels vehicle dynamics with nonlinear tire model is used as a mathematical model.

In the simulation study and experimental validation, the actuation dynamics will not be considered. They rely essentially on the current control of electric motors. So far, it is well known that the use of electric motors as actuators is one of the advantages of electric vehicles and at the same time presents a negligible short delay (i.e. a few ms) in the overall controlled system compared to the vehicle dynamics.

Fig. 12 depicts the simulation results with sinusoidal front steering angle input when the road friction coefficient is 0.3 and the vehicle is running at a speed of 100km/h. This can represent a critical driving situation of continuous lane change maneuver on slippery road. If the control is set off,  $\beta$  can assume larger values causing the vehicle to loose its stability and unable to accomplish the lane change as in normal situations (Fig. 13). With the proposed hybrid observer an accurate estimation of body slip angle is obtained. By applying DYC based on the hybrid observer, the yaw rate  $\gamma$  is successfully controlled to the desired value and the body slip angle  $\beta$  is guaranteed to be limited. However, if DYC was based on the linear observer, the incorrect estimation of body slip angle will lead to control deterioration.

Fig.14 is the  $\beta - \gamma$  phase plane trajectory related to the simulation results. Under DYC control, a limited trajectory loop is drawn by the vehicle within the stable area defined for our vehicle. Without  $\beta$  control, this trajectory of  $\beta - \gamma$  phase plane can not be satisfied and become much larger until the vehicle leaves the stable area putting the passengers in danger.



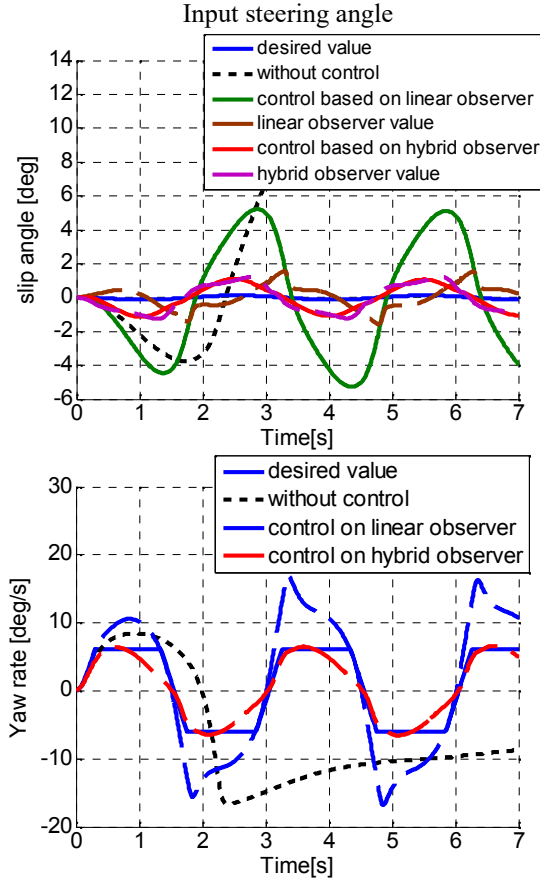


Fig.12 Slip angle (top panel) and yaw rate (bottom panel) under  $\beta$  control.

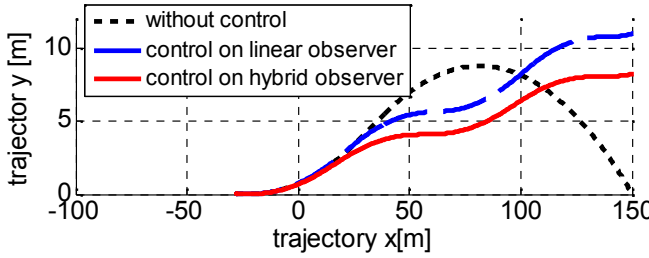


Fig.13 Vehicle trajectory with and without  $\beta$  control.

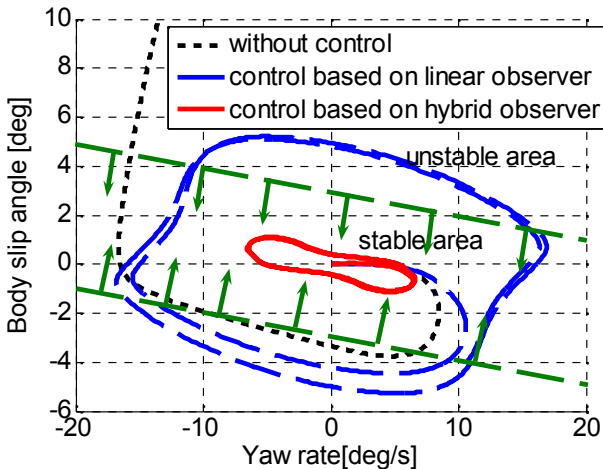


Fig.14 Control trajectories in  $\beta - \gamma$  phase plane.

## VI. CONCLUSION

This paper presented an algorithmic solution of the nonlinear vehicle dynamic control problem which has been validated both in a simulation environment and real-time. A state observer has been designed for an in-wheel-motored electric vehicle with Direct Yaw-moment Control (DYC) using fuzzy modeling techniques. Takagi-Sugeno (T-S) fuzzy models were employed for approximating the nonlinear vehicle dynamics with linear local models. An adaptation mechanism was introduced to adjust the fuzzy membership functions in response to changes in road friction conditions. The local observers design was based on Kalman filter theory and was combined with an interpolating mechanism which provided the link between the underlying local dynamics. The quantitative accuracy and adaptation performance of the proposed observer has been verified in simulations and experimentally. We have shown that the designed controller rely critically on the estimated value of  $\beta$  and further research and effort will be devoted into the implementation of a full dynamic stability control of the UOT MARCH II.

## APPENDIX

### Description of “UOT MARCH II”

The Electric Vehicle named : “UOT (University of Tokyo) Electric March II” was constructed in 2001. The most special feature of this EV is the in-wheel motor mounted in each wheel. We can control each wheel torque completely and independently. Regenerative braking is also available. Former researchers from Hori Laboratory at the University of Tokyo contributed to build this EV by remodeling a Nissan March. Fig. A1 shows a sketch of the “UOT MARCH II”.

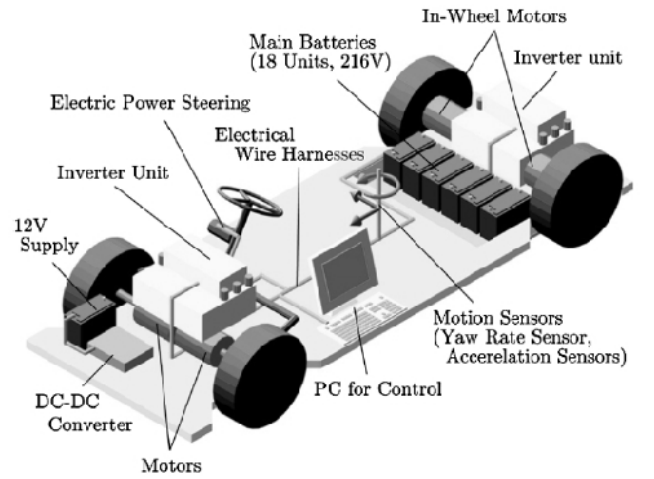


Fig. A1 Sketch of the “UOT MARCH II”.

TABLE I



SPECIFICATIONS OF "UOT ELECTRIC MARCH II"

Drivetrain	4 PM Motors / Meidensya Co.
Max. Power(20 sec.)	36 [kW] (48.3[HP])*
Max. Torque	77* [Nm]
Gear Ratio	5.0
Battery	Lead Acid
Weight	14.0 [kg](for 1 unit)
Total Voltage	228 [V] (with 19 units)
Base Chassis	Nissan March K11
Wheel Base	2360 [m]
Wheel Tread F/R	1365/1325 [m]
Total Weight	1400 [kg]
Wheel Inertia**	8.2 [kg]***
Wheel Radius	0.28 [m]
Controller	
CPU	MMX Pentium 233[MHz]
Rotary Encoder	3600 [ppr]***
Gyro Sensor	Fiber Optical Type

\* ... for only one motor. \*\* ... mass equivalent.

\*\*\* ... affected by gear ratio.

Fig. A2 displays photos describing the main parts of the vehicle developed in our laboratory.

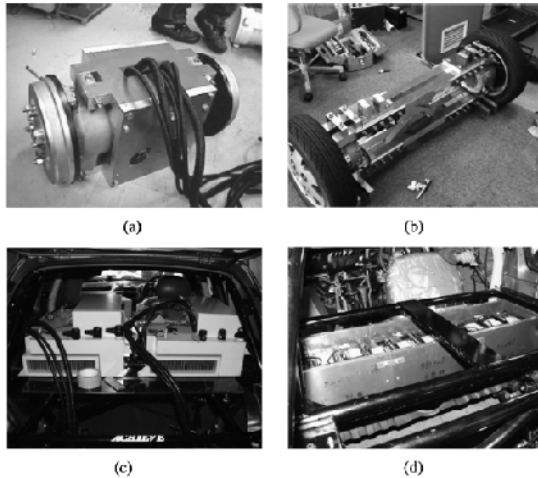


Fig. A2 Photos of the vehicle: (a) front motors, (b) rear motors, (c) inverters, (d) batteries.

## VII. REFERENCES

- Yoichi Hori, "Future Vehicle Driven by Electricity and Control Research on 4 Wheel Motored "UOT March II" ", in AMC2002 Proc. (7th International Workshop on Advanced Motion Control Proceedings), pp.1-14, 2002.
- Donghyun Kim, Sungho Hwang, and Hyunsoo Kim, "Vehicle Stability Enhancement of Four-Wheel-Drive Hybrid Electric Vehicle Using Rear Motor Control", IEEE Trans. On Vehicular Technology, Vol. 57, no. 2, 727-735, March 2008.
- Keiyu Kin, Osamu Yano and Hiroyuki Urabe, "Enhancements in Vehicle Stability and Steerability with Slip Control", JSAE Review 24, pp. 71-79, 2003.
- M. Canale, L. Fagiano, A. Ferrara, C. Vecchio, "Vehicle Yaw Control via Second-Order Sliding-Mode Technique," IEEE Trans. on Industrial Electronics, vol. 55, no. 11, pp. 3908-3916, Nov 2008.
- N. Mutoh, Y. Hayano, H. Yahagi, K. Takita, "Electric Braking Control Methods for Electric Vehicles With Independently Driven Front and Rear Wheels," IEEE Trans. on Industrial Electronics, vol. 54, no. 2, pp. 1168-1176, April 2007.
- Christoph Arndt, Johannes Karidas and Rainer Busch, "Design and Validation of a Vehicle State Estimator", Proc. Of AVEC'04 ( The 7<sup>th</sup> International Symposium on Advanced Vehicle Control), pp. 41-45, 2004.
- L. Imsland, T.A. Johansen, T.I. Fossen, etc, "Vehicle Velocity Estimation Using Nonlinear Observers", Automatica, Vol.42, pp. 2091-2103, 2006
- F. Cheli, E. Sabbion, M. Pesce, S. Melzi, "A Methodology for Vehicle Sideslip Angle Identification: Comparison with Experimental Data", Vehicle System Dynamics, Vol.45, No.6, pp. 549-563, June 2007.
- T. A. Wenzel, K. J. Burnham, etc, "Motion Dual Extended Kalman Filter for Vehicle State and Parameter Estimation", Vehicle System Dynamics, Vol.44, No.2, pp. 153-171, February 2006.
- Haddoun, A.; El Hachemi Benbouzid, M.; Diallo, D.; Abdessemed, R.; Ghouili, J.; Srairi, K., Modeling, Analysis, and Neural Network Control of an EV Electrical Differential. *IEEE Trans. Ind. Elec.*, Vol. 55, No.6, pp. 2286-2294, Oct. 2008.
- R. Babuska and H. Verbruggen, "An Overview of Fuzzy Modeling for Control", Control Engineering Practice, vol. 4, no. 11, pp. 1593 – 1606, 1996.
- Dan Simon, "Kalman filtering for fuzzy discrete time dynamic systems", Applied Soft Computing 3, pp. 191–207, 2003.
- Yoshifumi Aoki, Toshiyuki Uchida and Yoichi Hori, "Experimental Demonstration of Body Slip Angle Control based on a Novel Linear Observer for Electric Vehicle", in IECON2005 Proc. (The 31st Annual Conf. of the IEEE Industrial Electronics Society Proceedings), pp.2620-2625,2005.
- Liu, Ch.Sh. and Peng, H., "Road Friction Coefficient Estimation For Vehicle Path Prediction", Vehicle System Dynamics, Vol.25 Suppl., pp. 413-425, 1996.
- Y. Hori, Future Vehicle Driven by Electricity and Control- Research on Four Wheel Motored "UOT MARCH II". *IEEE Trans. Ind. Elec.*, Vol. 51, No.5, pp. 954-962, Oct. 2004.
- J. Th. Paul, Venhovens, K. Naab, "Vehicle Dynamics Estimation Using Kalman Filters", Vehicle System Dynamics, Vol.32, pp. 171-184, 1999.
- M.C. Best, T.J. Gordon and P.J. Dixon, "An Extended Adaptive Kalman Filter for Real-time State Estimation of Vehicle Handling Dynamics", Vehicle System Dynamics, Vol.34, pp. 57-75, 2000.
- R. E .Kalman, "New Result in Linear Filtering and Prediction Theory", J.Basic Eng., Trans. ASME, Ser. D, 83, pp.95-108.
- Geng Cong and Hori Yoichi, "Nonlinear Body Slip Angle Observer for Electric Vehicle Stability Control", in EVS23 Proc. (23rd International Electric Vehicle Symposium and Exposition), 2007.
- Cong Geng, Toshiyuki Uchida and Yoichi Hori, "Body Slip Angle Estimation and Control for Electric Vehicle with In-Wheel Motors", in IECON2007 Proc. (The 33rd Annual Conf. of the IEEE Industrial Electronics Society Proceedings), pp.351-355, 2007.



**C. Geng**, received M.S. degree in Vehicle Engineering from JiLin University of Technology in 1996 and joined the Department of Transportation and traffic as an Assistant Professor and became a lecturer in 1999. Then she worked in Beijing Jiaotong University as a lecturer from 2000. She is a Ph.D student of the University of Tokyo from 2006. She is interested in vehicle dynamics analysis and control technology. Now her studies focus on the advanced motion control of electric vehicle.



**L. Mostefai** received a master degree in Electrical Control Engineering in 2002. He has been giving lectures on "Control Engineering" and "Microprocessors and Microcontrollers in Industrial

applications” at the University Moulay Tahar in Saida, Algeria. He joined HORILAB at the Institute of Industrial Science, the University of Tokyo, as a research student in 2006. He is currently a PhD student at Mohamed Boudiaf University of Science and the Technology of Oran (USTO). His interests mainly are on: optimal and robust control, motion control systems, smart materials and their application, automotive engineering and renewable energies.



**M. Denaï** received his Bachelor in Electrical Engineering in 1982 from the university of Algiers (Algeria) and his PhD in Control Engineering from the University of Sheffield (UK) in 1988. He is Professor at the University of Science and the Technology of Oran (USTO). Currently he is on a research leave at the Dept of Automatic Control and Systems Engineering, University of Sheffield (UK). His main field of interest are intelligent control design, intelligent fault detection in power systems, advanced control of power devices, modeling and control of electric power systems,

modeling, simulation and control design for efficiency optimisation in the field of renewable energies such as solar, wind, investigation of power electronics interface for renewable energy systems, modeling and control of life science systems, data mining and knowledge discovery for system modeling.



**Y. Hori** was born on 14 July, 1955. He received the B.S., M.S. and Ph.D. degrees in Electrical Engineering from the University of Tokyo in 1978, 1980 and 1983, respectively. In 1983, he joined the University of Tokyo, the Department of Electrical Engineering as a Research Associate. He later became an Assistant Professor, an Associate Professor, and in 2000 a Professor. In 2002, he moved to the Institute of Industrial Science, the University of Tokyo, as a Professor of Information & Electronics Division, Electrical Control System Engineering. During 1991-1992,

he was a visiting researcher at the University of California, Berkeley (UCB). He was the Treasurer of IEEE Japan Council and Tokyo Section during 2001-2002. He is now an AdCom member of IEEE-IES. He was the Vice President of IEE-Japan IAS in 2004-2005. He has been the chairman of ECaSS (Energy Capacitor Storage System) Forum, and the chairman of Motor Technology Symposium of JMA. His research fields are control theory and its industrial application to motion control, mechatronics, robotics, electric vehicle, etc. He is a member of IEE-Japan, JSME, SICE, RSJ, SAEJ, JSST and so on. IEEE Fellow. He is the winner of the Best Transaction Paper Awards in IEEE Trans. on Industrial Electronics in 1993 and 2001, and so on.